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ANALYSIS OF LAND COVER CHANGE IN MOROWALI USING LANDSAT 8 SATELLITE IMAGERY AND UNSUPERVISED CLASSIFICATION METHOD

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ABSTRACT
Land use changes reflect the ecological and socio-economic dynamics of a region. This study aims to analyze land cover changes using Landsat 8 satellite imagery with the unsupervised classification method. Land cover is categorized into five classes: light vegetation, dense vegetation, rice fields, plantations, and settlements and mining areas. The analysis was conducted by comparing data from 2013 and 2018. The results indicate a significant increase in the area of mining and settlements by 71.60 km² and 476.88 km², respectively. Conversely, the area of rice fields and light vegetation decreased by 1117.93 km², natural canopy decreased by 672.03 km², and plantations decreased by 524.84 km². These findings indicate land conversion from natural vegetation to non-vegetative areas due to mining industry expansion and settlement growth. This study provides valuable insights for more sustainable land-use planning in the future

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1. INTRODUCTION

Land cover change is a crucial issue frequently driven by mining activities. These activities not only alter the natural landscape but also significantly impact local ecosystems and communities. A study by Purnama et al. (2024) indicated that the use of remote sensing imagery is effective in mapping and analyzing land cover changes in the Kupang Tengah Subdistrict, East Nusa Tenggara [1].

Spatial analysis of land cover change in coal mining areas shows that the rate of land transformation is proportional to population and economic growth in the surrounding area. This affirms that mining activities have a direct correlation with the dynamics of land use changes [2].

Furthermore, research by Zulkarnain (2015) highlighted that the presence of mining sites is often followed by population growth, both through natural increase and migration [3]. This phenomenon implies a rising demand for land for settlements and other needs, ultimately leading to shifts in land use.

On the other hand, the application of remote sensing technology and unsupervised classification methods has been used to analyze land cover in Sawahlunto City, West Sumatra [4]. This approach enables more accurate and efficient identification of land cover changes due to mining activities.

Based on a review of the literature, several research gaps remain underexplored:

1. The lack of comprehensive geospatial studies in major mining areas such as Morowali that utilize a combination of unsupervised classification methods and vegetation indices.
2. Few studies have specifically compared multi-temporal Landsat 8 satellite imagery to quantify land cover changes due to mining industry expansion.
3. A deficiency in accuracy-based analysis (e.g., confusion matrix) in land cover change studies in Indonesia, resulting in previous findings being less quantitatively verified.

This study aims to address the above gaps using the following approaches:

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1. Applying a combination of NDVI and ISO Cluster methods in ArcGIS to analyze land cover changes caused by mining activities.
2. Providing quantitative data based on Landsat 8 imagery from 2013 and 2018 to map detailed spatial dynamics in Morowali Regency.
3. Presenting empirical evidence related to environmental degradation that can be used as a basis for formulating sustainable spatial planning policies.

Remote sensing has become an effective tool in monitoring land cover changes both spatially and temporally. Landsat 8 satellite imagery, with its high spectral resolution and periodic capture capabilities, allows for time-series land change analysis. The unsupervised classification technique using the ISO Cluster algorithm is employed in this study, as it can group pixels based on spectral similarity without requiring extensive reference data. With this method, changes in mining areas, deforestation, and other land use conversions can be identified more accurately.

In addition to environmental impacts, land cover changes due to mining also have social and economic consequences. Many local communities are directly affected—through the loss of agricultural land, clean water sources, and exposure to air and water pollution. Therefore, this research is expected to provide recommendations for local governments, mining companies, and communities in managing natural resources sustainably and minimizing the negative impacts of mining activities in Morowali.

To address the issue of land cover degradation caused by mining in Morowali, this research proposes a monitoring and evaluation system based on satellite imagery and unsupervised classification algorithms. Through this approach, the following can be achieved:

a. Rapid identification of vegetation degradation using Landsat 8 imagery through radiometric correction and the calculation of vegetation indices (NDVI and VIDN).
b. Land cover classification using ISO Cluster without training data (unsupervised), resulting in land mapping into five main classes.
c. Spatial and statistical analysis to assess the area change in each land cover class and its environmental implications.

Furthermore, this study will compare Landsat 8 imagery from multiple time periods to identify temporal patterns of land cover change. Thus, the extent of mining expansion and its environmental impacts can be assessed. The findings of this research are expected to encourage more serious efforts in spatial planning, post-mining land reclamation, and more sustainable environmental management in Morowali Regency.

2. LITERATURE REVIEW

A. Profile of Morowali Regency

Morowali Regency is located in Central Sulawesi Province, Indonesia, with its capital in Bungku Tengah Subdistrict. The regency covers an area of 5,472.00 km² and had a population of 170,415 as of June 30, 2022.

Geographically, the region consists of 132 coastal villages, 14 villages located along rivers or in valleys, 29 villages on slopes or hills, and 65 villages in inland areas. Morowali Regency is bordered by the waters of Tomori Bay and Tolo Bay and contains forested areas and mountain valleys.

Morowali is one of Indonesia's largest nickel-producing regions. Bahodopi Subdistrict serves as the center of nickel mining due to its significant nickel ore deposits. This mining industry plays a vital role in the local economy but also brings environmental impacts, such as landscape alteration and decreased water quality due to mining activities.

In addition, nickel mining operations in Morowali have affected the maritime environment, leading to coastal sedimentation and mangrove forest degradation, which in turn impacts the income of local fishermen. To address these impacts, it is crucial for the government and mining companies to incorporate waste management and environmental considerations into every mining plan, in order to maintain ecosystem balance and support the well-being of the local community.

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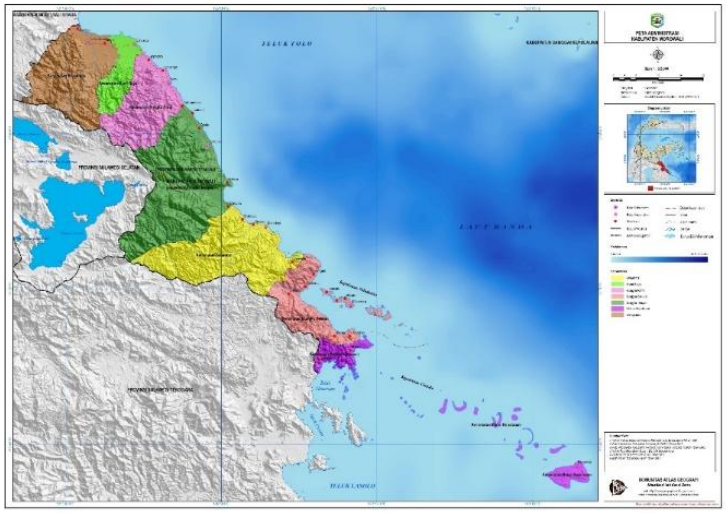

Image 1. Administrative Map of Morowali

B. State of The Art (SOTA)

Various studies have utilized remote sensing technology and Geographic Information Systems (GIS) to monitor land cover changes:

- **Purnama et al. (2024)** used remote sensing imagery to analyze land cover changes in non-mining areas (Kupang Tengah).
- **Zulkarnain (2015)** and **Dahlia et al. (2021)** highlighted the relationship between mining activities and population growth as well as socio-economic changes, but did not fully integrate this with comprehensive spatial analysis.
- **Cahyono et al. (2019)** applied unsupervised classification methods to land cover analysis in Sawahlunto City, but did not incorporate vegetation indices such as NDVI in their analysis.
- Several international studies have employed the **ISO Cluster algorithm** and **vegetation indices** to detect land degradation, yet local contexts such as in Morowali remain underexplored.

No	Researcher & Year	Study Area	Classification Method	Data Source	Gap/Limitation	Relevance to This Study
1	Purnama et al. (2024)	Kupang Tengah, NTT	Supervised	Landsat 8	Not focused on mining, did not use NDVI/ISO Cluster	Demonstrates general effectiveness of remote sensing
2	Zulkarnain (2015)	General mining areas	Not specified	Not stated	Do not use NDVI and spatial classification methods	Highlights link between mining and population migration
3	Dahlia et al. (2021)	Ombilin & Sangatta	Not specified	Not explained	Spatial analysis is limited; the focus is on socio-economic aspects.	Emphasizes importance of economic growth influence
4	Cahyono et al. (2019)	Sawahlunto, west sumatra	Unsupervised	Landsat	NDVI is not combined, and no accuracy assessment is conducted.	Provides validation that the ISO Cluster method is appropriate for land cover classification in mining regions
5	Polina et al. (2021)	Reykjavik	ISO Cluster + NDVI	Landsat TM	International studies, not focused on mining	Provides confirmation of the effectiveness of ISO

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						Cluster in analyzing land cover change
6	This Study	Morowali	Unsupervised ISO Cluster + NDVI & VIDN	Landsat 8 (2013–2018)	Local focus, temporal analysis, combined method	A combination of approaches and local application with detailed quantitative analysis.

C. Remote Sensing

Remote sensing is a widely utilized method in environmental studies and natural resource mapping. This technology enables the analysis of various aspects of the Earth's surface through satellite imagery that captures the spectral reflectance data of surface objects. It facilitates the monitoring of environmental changes such as deforestation, agricultural land expansion, and mining activities. Furthermore, remote sensing plays a crucial role in tracking land cover changes, which helps to identify environmental transformations and their underlying causes, thereby supporting sustainable resource management and mitigation efforts. [5]

Satellite imagery used in land cover change analysis varies based on spatial, spectral, and temporal resolution. Some commonly used satellites include:

- **Landsat 8**: Provides medium-resolution data (~30 meters), suitable for long-term temporal analysis.
- **Sentinel-2**: Offers higher spatial resolution (~10 meters) and wide spectral coverage, commonly used for environmental mapping.
- **MODIS**: Appropriate for global-scale monitoring due to its high temporal frequency, despite its lower spatial resolution.

D. Land Cover

Land cover refers to the physical and biogeochemical condition of the Earth's surface, encompassing both natural elements such as forests, rivers, and barren lands, and man-made features such as settlements and agricultural fields. Land cover is distinct from land use, which relates to how land is utilized by humans. Remote sensing is frequently employed to map and monitor land cover changes to support spatial planning, environmental conservation, and disaster mitigation efforts.

Land cover may be defined as the observable biophysical layer on the Earth's surface, shaped by human regulation, activities, and interventions aimed at production, maintenance, or alteration of a given area. [6]

E. Land Use

Land use refers to the organization and management of land by humans for various purposes such as residential development, agriculture, industry, mining, and recreation. It reflects human–environment interactions in utilizing space to meet societal needs. Land use changes can significantly affect ecosystems and environmental equilibrium. Therefore, effective land use planning is essential to ensure the sustainable use of natural resources and to minimize negative environmental impacts.

Land use also provides insights into areas with development potential based on scientific assessments and space allocation regulated by regional spatial planning documents. [6] Furthermore, other studies suggest that land use is an expression of human activities conducted on land as part of efforts to sustain human livelihoods.

F. ArcGIS

ArcGIS is a Geographic Information System (GIS) software developed by the Environmental Systems Research Institute (ESRI). It is used to acquire, manage, analyze, and visualize spatial data. ArcGIS offers a wide range of tools for mapping and analyzing geospatial information, supporting applications such as urban planning, natural resource management, and environmental monitoring. Additionally, ArcGIS allows for the integration of spatial and non-spatial data, thereby facilitating more effective location-based decision-making.

A study has noted that ArcGIS is among the most popular and reliable platforms for performing GIS-related tasks. [7] It is a specialized software system for processing cartographic information and Earth-surface–based data. [8] Owing to its extensive capabilities, ArcGIS has become a fundamental tool in geospatial research and applications across diverse disciplines.

G. Image Classification

Image classification is the process of grouping pixels in a digital image into specific categories or classes based on their spectral or textural characteristics. This process aims to identify and map objects or features present in imagery, such as land cover types, land use patterns, or other specific surface elements. In remote sensing, image classification is a key method for analyzing satellite data and generating relevant geospatial information.

Several classification methods are commonly used, including:

1. **Pixel-Based Classification**: This method analyzes each pixel individually based on its spectral value, without considering its spatial context. It is commonly applied to imagery with lower spatial resolution.
2. **Object-Based Image Analysis (OBIA)**: This approach groups adjacent pixels into objects and analyzes their shape, texture, and spatial relationships. It is particularly effective for high-resolution imagery where spatial detail is critical.
3. **Scene-Based Classification**: This method interprets the entire scene or contextual pattern within the image to classify areas based on broader spatial characteristics. It is useful for complex imagery with diverse features.

Advances in remote sensing technology have facilitated the transition from pixel-based classification to object- and scene-based methods, driven by improvements in satellite image resolution and quality. The appropriate classification technique should be selected based on the analysis objectives, image resolution, and study area characteristics.

One study identifies three major paradigms in remote sensing image classification—pixel-based, object-based, and scene-based approaches. [9] In addition, other research indicates that classification is aimed at distinguishing among predefined categories and labels. [10]

Thus, understanding and appropriately applying classification methods is essential to producing accurate geospatial information and supporting a wide range of applications, including spatial planning, environmental monitoring, and natural resource management.

H. ISO Cluster

The ISO Cluster algorithm is an unsupervised classification method used in remote sensing image analysis to group pixels with similar spectral characteristics into several clusters. The process is iterative and aims to minimize the Euclidean distance between pixels and their assigned cluster centers. ISO Cluster implements the Iterative Self-Organizing Data Analysis Technique (ISODATA), an enhancement of the K-Means algorithm. A key distinction is that ISODATA can increase or decrease the number of clusters during iterations based on specific criteria, such as cluster size or inter-cluster distance. [11]

In general, the ISO Cluster algorithm operates through the following steps:

1. **Initialization**: Establish initial cluster centers randomly or based on prior information.
2. **Clustering**: Assign each pixel to the nearest cluster center using Euclidean distance in multi-dimensional spectral space.
3. **Cluster Center Update**: Recalculate cluster center positions as the mean of all pixels within the cluster.
4. **Iteration**: Repeat the clustering and updating steps until convergence is reached, which occurs when cluster center movements between successive iterations fall below a defined threshold or a maximum number of iterations is met.

Throughout the iteration process, the algorithm may adjust the number of clusters by splitting high-variance clusters or merging those that are spectrally similar and spatially proximate. This feature allows for greater flexibility in determining the optimal number of clusters according to the characteristics of the dataset under analysis. [11] The main formula used in this method is:

1. **Covariance Matrix**:

$$\Sigma = \frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})(X_i - \bar{X})^T$$

- Determining the relationship among spectral variable in the image.
- Σ represents the covariance matrix,
- X_i denotes the i-th pixel vector, and
- X^- is the mean pixel vector within the cluster.

2. **Cluster Mean**:

$$C_j = \frac{1}{n}\sum_{i=1}^{n} X_i$$

- Determines the cluster center based on the mean value of pixels within the group.
- C_j represents the center of the -j cluster
- X_i is the value of the-i pixel within the cluster
- n is the number of pixels in the cluster.

3. **Mahalanobis Distances**:

$$D_M = \sqrt{(X-\mu)^T\Sigma^{-1}(X-\mu)}$$

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- Determines how close a pixel is to a specific cluster center.
- D_M denote the Mahalanobis distance
- X represent the feature vector of the pixel
- μ be the cluster center vector
- Σ^{-1} be the inverse of the covariance matrix.

The ISO Cluster method in ArcGIS is employed to group pixels based on their statistical distribution within a multidimensional space. Unlike other methods, ISO Cluster optimizes the number of clusters according to the data distribution.
The implementation of the ISO Cluster algorithm can be found in software such as ArcGIS, where this tool is used to classify raster data into several classes based on their spectral distribution without requiring reference or training data beforehand.
Therefore, the ISO Cluster algorithm is an effective tool for remote sensing data analysis, particularly in situations where prior information about the classes within the image is limited or unavailable. A study conducted by Polina et al. (2021) [12] demonstrated that this method can accurately detect land cover changes, especially when used in combination with vegetation indices such as NDVI.

I. NDVI (Normalized Difference Vegetation Index)

The Normalized Difference Vegetation Index (NDVI) is an index used to monitor vegetation health and density by utilizing remote sensing data. NDVI is calculated based on the difference in reflectance between the red and near-infrared (NIR) spectral bands.
Healthy vegetation tends to absorb most red light for photosynthesis while reflecting a greater portion of near-infrared light. This contrast allows NDVI to distinguish areas with dense, sparse, or no vegetation.
The NDVI formula is expressed as:

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

Where:

- **NIR**: Near-infrared light reflectance
- **Red**: Red light reflectance

NDVI values range from -1 to 1. Values approaching 1 indicate dense and healthy vegetation; values around 0 typically represent areas with little to no vegetation, such as bare soil or rocky surfaces; while values nearing -1 correspond to surfaces like water bodies, snow, or clouds. NDVI has a wide range of applications, including monitoring land cover changes, assessing plant health, and managing natural resources. By utilizing satellite imagery, NDVI enables efficient and accurate spatial analysis of vegetation conditions across various spatial scales.
Based on previous studies, it can be concluded that land cover analysis related to mining activities heavily depends on the classification techniques employed. Vegetation index-based methods such as NDVI provide a general overview of land cover changes, while machine learning and statistical analysis methods yield more detailed and accurate results. In this study, the ISO Cluster approach is employed as the classification method to identify land cover change patterns caused by mining activities in Morowali Regency. This approach is expected to produce more accurate insights into the environmental impacts and serve as a foundation for more sustainable land management planning.

3. RESEARCH METHODOLOGY

The type of data used in this study is **quantitative data**. Quantitative data refers to information expressed in numerical form, allowing for mathematical processing and objective analysis to draw conclusions. In this research, quantitative data are derived from calculations of vegetation indices and the area of each land cover class, based on the processing of **Landsat 8 satellite imagery**. The data used are **secondary data**, specifically Landsat 8 satellite imagery that has undergone **radiometric correction and classification** processes.

Data type	Source	Descrition
Satellite Imagery	USGS Earth Explorer	Landsat 8 OLI/TIRS for the years 2013 and 2018
Administrative Shapefile	BIG/OpenStreetMap	Administrative boundaries of Morowali Regency
RBI Map	Geospatial Information Agency	Reference for spatial validation
Secondary Data	Previous studies & SNI references	Supporting classification and accuracy assessment

The variables in this study consist of two types: independent and dependent variables. The independent variable is the Landsat 8 satellite imagery, which serves as the primary source for the analysis. Meanwhile, the dependent variables include the vegetation index values and the changes in land cover categories (light vegetation, forest canopy, settlements and mining areas, water bodies, and degraded land) over a specific time period. Land cover

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change is analyzed through image classification, with the land cover categories grouped into four main classes: forest, mining area, water body, and settlement. Figure 2 illustrates the workflow employed in this study. The preparation stage involves the acquisition and correction of satellite imagery used in the analysis.

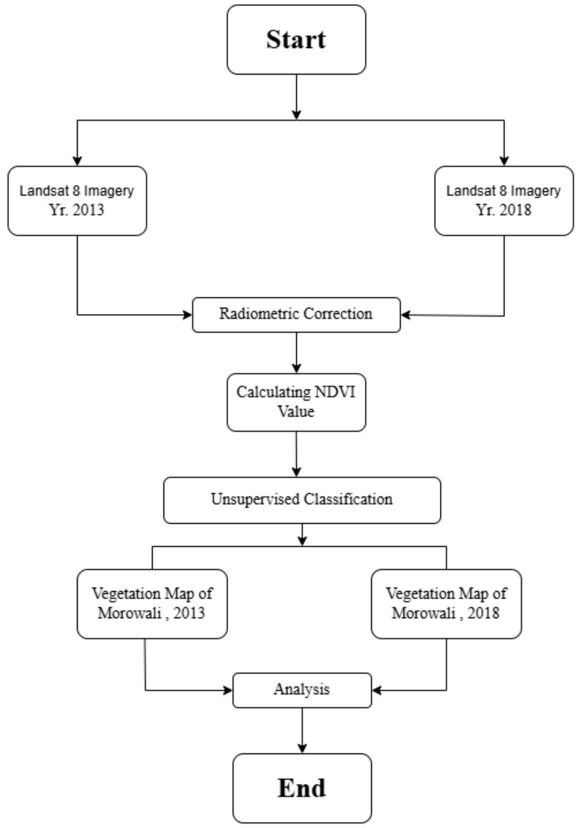

Image 2. Research Workflow Diagram

Landsat 8 Imagery Acquisition

In this study, the primary data used are Landsat 8 OLI/TIRS satellite images, obtained from the United States Geological Survey (USGS) via the Earth Explorer platform. The imagery includes data from the years 2013 and 2018, selected to identify patterns of land cover change over a specific time period. Landsat 8 imagery has a spatial resolution of 30 meters, which is adequate for conducting land cover analysis at the regional scale.

Landsat 8 consists of several spectral bands, with this study focusing particularly on the red band (Red), near-infrared (NIR), and shortwave infrared (SWIR). The red band is useful for detecting vegetation characteristics and open land, while the near-infrared band is particularly effective in distinguishing healthy vegetation from non-vegetated areas. The shortwave infrared band is employed to identify soil conditions and moisture levels, which are highly relevant for analyzing land changes caused by mining activities.

In addition to satellite imagery, this study also utilizes the administrative boundary shapefile of Morowali Regency, obtained from the Geospatial Information Agency (BIG) or other spatial data sources such as OpenStreetMap. This data is used to delineate the study area, ensuring that the analysis only covers the territory of Morowali Regency and does not extend beyond it. To support the validation of classification results, the Indonesian Topographic Map (Peta Rupa Bumi Indonesia, RBI) is used as an additional reference.

Landsat Image Preprocessing

Data processing in this study was carried out in stages to ensure that the satellite imagery used was properly corrected and ready for analysis. These stages include radiometric correction, vegetation index calculation, land cover classification using the ISO Cluster method, and land cover change analysis.

Before classification, the satellite imagery underwent radiometric correction to improve image quality and reduce atmospheric effects. This correction was performed by converting the Digital Number (DN) values into Top of Atmosphere (TOA) reflectance. This conversion is essential because raw satellite imagery is often influenced by external factors such as solar angle, atmospheric thickness, and lighting conditions.

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TOA reflectance is calculated using the following equation**:**

$$R_{\lambda} = M_L Q_{cal} + A_L$$

In this equation, $R\lambda$ epresents the TOA reflectance, M_L is the band-specific reflectance multiplicative scaling factor obtained from the image metadata, $Qcal$ is the DN value of the corresponding pixel, A_L is the band-specific reflectance additive correction value. After converting to TOA reflectance, atmospheric correction is performed using the DOS method. This method aims to reduce the effects of atmospheric scattering by correcting the minimum reflectance values in the image. The correction is carried out using the following formula:

$$R_{\lambda,corr} = R_{\lambda} - R_{min}$$

Through radiometric correction, the resulting imagery becomes more accurate in representing surface conditions on Earth. The corrected images are then used to calculate vegetation indices to identify land cover changes resulting from mining activities.

Vegetation Index Calculation (NDVI & VIDN)

After the satellite imagery undergoes radiometric correction, vegetation index calculations are performed to assess the condition of vegetation and the changes that have occurred during the analyzed time period. This study utilizes two primary vegetation indices: the Normalized Difference Vegetation Index (NDVI) and the Vegetation Index Difference to Normal (VIDN).

NDVI is a widely used vegetation index for measuring the density and health of vegetation in a given area. The NDVI is calculated using the following formula:

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$$

In this equation, *NIR* (near-infrared) corresponds to Band 5 of Landsat 8, while RED (red) corresponds to Band 4. NDVI values range from -1 to 1, where positive values indicate the presence of vegetation, whereas lower or near-zero values represent areas with minimal vegetation or open land, such as mining areas.

In addition to NDVI, this study also employs the VIDN (Vegetation Index Difference to Normal) to measure changes in vegetation relative to its normal condition. VIDN is used to understand the extent to which vegetation has changed compared to reference values that represent healthy vegetation. The VIDN is calculated using the following formula:

$$VIDN = \frac{(NDVI_{max} - NDVI)}{NDVI_{max}}$$

Here, **NDVImax** represents the maximum NDVI value obtained from areas with vegetation in healthy condition. By calculating **VIDN**, the degree of vegetation degradation caused by mining activities can be identified.

Land Cover Classification and Change Analysis

The classification method applied in this study is **unsupervised classification,** which is a spectral-based image interpretation technique that does not require training data. This method is used to group pixels based on similarities in reflectance values, producing a GeoTIFF-type image with four main land cover classes: forest, settlement, mining area, and water bodies.

The analysis process begins with identifying the results of the **NDVI** and the land cover classification. The processed image data are then converted into numerical values to facilitate statistical calculations and further analysis. The NDVI results are presented in a table containing information on value ranges, averages, and the distribution of NDVI values for each land cover class. This table is then visualized in a graph showing NDVI value changes over the years, providing an overview of vegetation degradation caused by mining activities.

After calculating the vegetation index, land cover classification is carried out using the **ISO Cluster method** in ArcGIS. This method groups pixels based on their spectral distribution without requiring training data. During this process, spectral values are clustered to form several land cover classes. ISO Cluster utilizes statistical analysis with a covariance matrix to determine the data distribution within the generated clusters. The covariance matrix used is expressed by the following equation:

$$\Sigma = \frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})(X_i - \bar{X})^T$$

In addition, the determination of cluster centers is carried out by calculating the spectral mean of each cluster using the following formula:

$$C_j = \frac{1}{n}\sum_{i=1}^{n} X_i$$

The results of the unsupervised classification are presented in the form of land cover maps for each year of analysis. These maps provide a visual representation of the distribution of land cover classes in Morowali Regency for

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each respective period. In addition, a table showing the area of each land cover class for every observation year is also included. This table illustrates the extent of land area changes due to mining activities and other land use changes.

To ensure the accuracy of the classification results, an accuracy assessment was conducted using the Overall Accuracy method. The accuracy test is presented in the form of a confusion matrix table, which includes User Accuracy, Producer Accuracy, and Overall Accuracy, with an accuracy threshold of ≥ 80% for the classification results to be considered reliable. Based on this assessment, the classification accuracy level was obtained, indicating the extent to which the unsupervised classification method accurately represents the actual land cover conditions.

4. RESULTS AND DISCUSSION

Image Correction

The image correction process was conducted using QGIS 3.40 with the aid of the Semi-Automatic Classification Plugin (SCP) to enhance the quality of the imagery before further analysis. This correction aims to eliminate atmospheric disturbances and adjust reflectance values, thereby making the imagery more representative of actual conditions on the Earth's surface.

The correction stages included radiometric and atmospheric correction. Radiometric correction was performed to convert Digital Number (DN) values into reflectance values, ensuring a more accurate representation of object characteristics within the imagery. Following this, atmospheric correction was applied using a method designed to remove the effects of light scattering in the atmosphere, thereby minimizing spectral value discrepancies caused by external factors.

Using QGIS 3.40 and the SCP Plugin, the correction process could be carried out more quickly and efficiently due to automated features for extracting atmospheric parameters. After the correction phase was completed, the imagery was ready for vegetation index calculation and land cover classification. As a result, features within the radiometrically corrected imagery appeared more distinct (Figure 3).

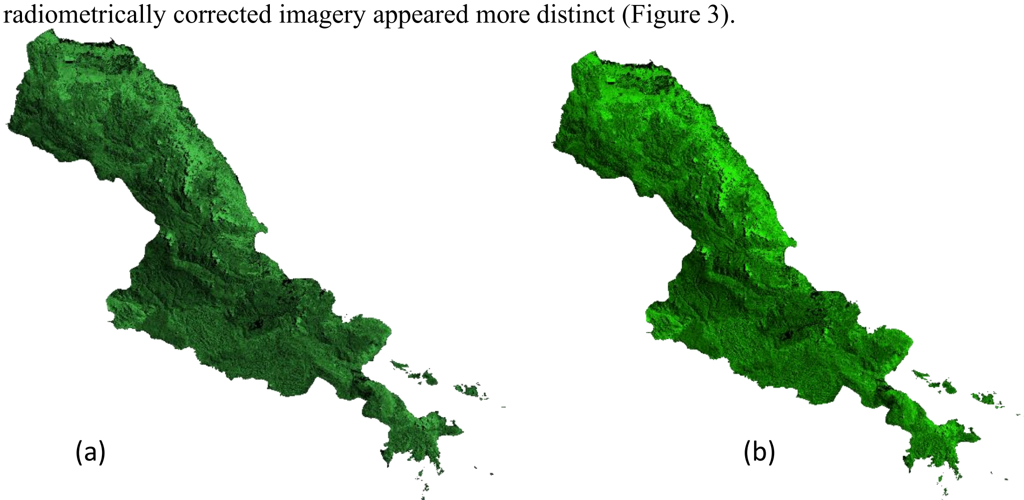

Image 3. True Color Composite Band Results (a) Before and (b) After Radiometric Correction (ToA)

NDVI

Figure 1 illustrates the change in median Normalized Difference Vegetation Index (NDVI) values between 2013 and 2018. There is a noticeable downward trend, with NDVI values decreasing from approximately 0.44 in 2013 to around 0.36 in 2018. This decline indicates a reduction in vegetation cover during the observed period. Several factors may have contributed to this change, including land conversion for settlements or mining activities, deforestation, and environmental changes such as drought or land degradation.

In general, lower NDVI values reflect a reduced presence of green vegetation, while higher values indicate denser and healthier vegetation cover. This decline in NDVI warrants further investigation through spatial analysis and the examination of additional environmental factors to better understand its impact on the local ecosystem.

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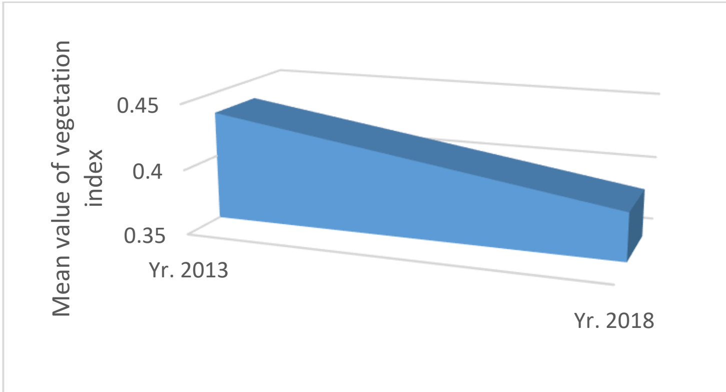

Graph 1. Median Vegetation Index (NDVI) Values of Morowali Regency in 2013 and 2018

Meanwhile, the NDVI value map (**Figure 4**) for the same study area in Morowali Regency shows that several regions previously represented in green (indicating high NDVI values) have shifted to red, signifying a decrease in NDVI values. This change may be attributed to reduced vegetation cover caused by anthropogenic activities such as settlement expansion, mining operations, or other land use changes. Additionally, the decline could be influenced by environmental factors such as prolonged dry seasons or land degradation.

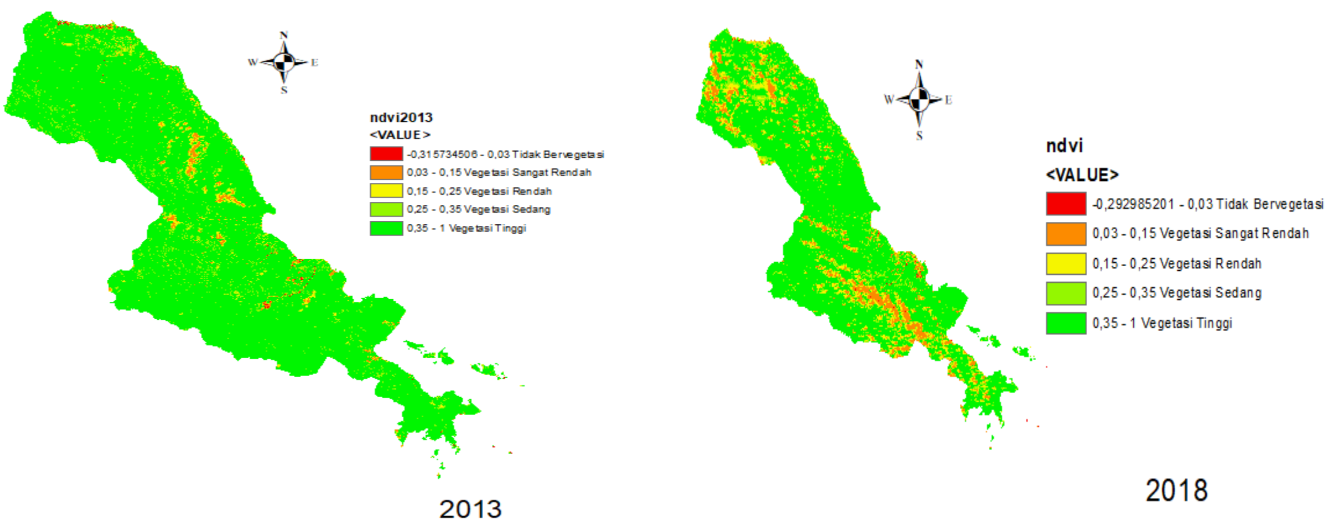

Image 4. NDVI Map of Morowali Regency in 2013 and 2018

Land Cover Classification

Land cover classification in Morowali Regency was carried out using the *unsupervised classification* method applied to Landsat 8 imagery. The classification process utilized an RGB band combination (Red, Green, and Blue), derived from the composite of Band 2 (Blue), Band 3 (Green), and Band 4 (Red). This band combination allows for the identification of land cover types based on the spectral reflectance differences of various surface features.

The result of the unsupervised classification is a series of land cover maps for each year analyzed, following radiometric correction procedures. The classification output is categorized into five major land cover classes: degraded land, paddy fields and sparse vegetation, forest canopy, local plantations, and residential and mining areas.

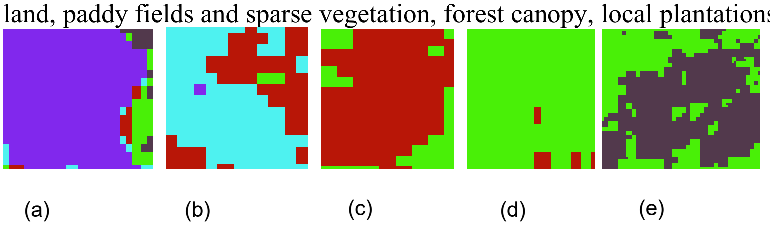

Image 5. Example of Surface Feature Appearance Based on Classification Results, including (a) Degraded Land, (b) Rice Fields and Sparse Vegetation, (c) Forest Canopy, (d) Local Plantations, and (e) Settlements and Mining Areas.

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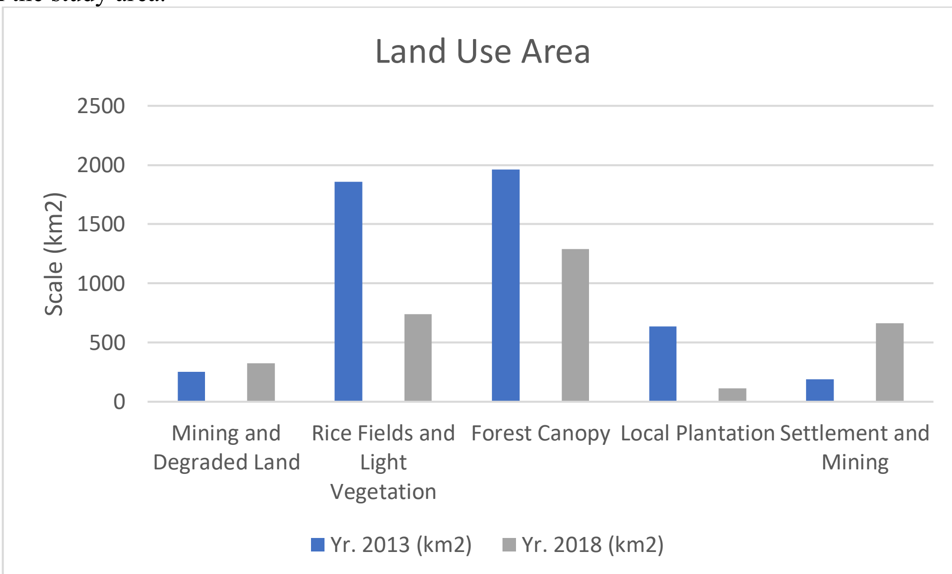
Based on the results of the unsupervised classification, the next step is to calculate the area of each land cover class. The area is calculated by multiplying the number of pixels in each class by the area represented by each pixel. Since the imagery used is from Landsat 8 with a spatial resolution of 30 m × 30 m, each pixel represents an area of 900 m². Therefore, the total area for each land cover class can be determined based on the number of pixels identified in each category. The results of these calculations are used to analyze land cover changes and the distribution of land classes within the study area.



Graph 2. Land Use Area of Morowali Regency

Based on the data presented in the graph, there was a significant change in land use between 2013 and 2018. The *forest canopy* category experienced a substantial decrease in area, indicating deforestation or land conversion to other uses. Conversely, the area classified as *Residential and Mining* showed a notable increase, reflecting the expansion of mining zones and the development of settlements due to population growth and economic activity.

Meanwhile, the *Paddy Fields and Sparse Vegetation* category also showed a decline in area, likely caused by the conversion of agricultural land into residential or mining areas. The *Local Plantation* category experienced a slight increase, indicating an expansion in the plantation sector. *Mining and Degraded Land* also expanded, suggesting that mining activities in the region have intensified over the five-year period.

These changes in land use patterns may impact ecosystem balance and regional land management. The expansion of mining and residential areas potentially reduces vegetation cover and increases the risk of environmental degradation.

The following is the calculated difference in land use changes between 2013 and 2018 based on the data:

Table 1. Land Area Changes

Descrition	Year 2013 (km²)	Year 2018 (km²)	Difference (km²)
Mining and Degraded Land	254.02	325.61	+71.59
Rice Fields and Light Vegetation	1858.48	740.55	-1117.92
Forest Canopy	1963.90	1291.87	-672.03
Local Plantation	638.11	113.27	-524.84
Settlement and Mining	188.19	665.07	+476.87

From the table above, it is evident that there has been a significant increase in the categories of mining and degraded land as well as settlement and mining, reflecting the expansion of mining activities and residential development. Meanwhile, there has been a reduction in the area of rice fields and light vegetation, forest canopy, and local plantation, indicating a conversion of agricultural and forest land into non-vegetated areas.

The land cover classification map of Morowali Regency for the year 2018 is shown in Figure 5. From this map, the distribution of various types of land cover across the Morowali region can be clearly observed. Several major categories identified include light vegetation, forest canopy, local plantations, and settlement and mining areas. In addition, mining and degraded land areas are also dispersed across several locations. This map provides an overview of land cover changes and conditions that can be used for further analysis regarding environmental impacts and regional development in Morowali Regency.

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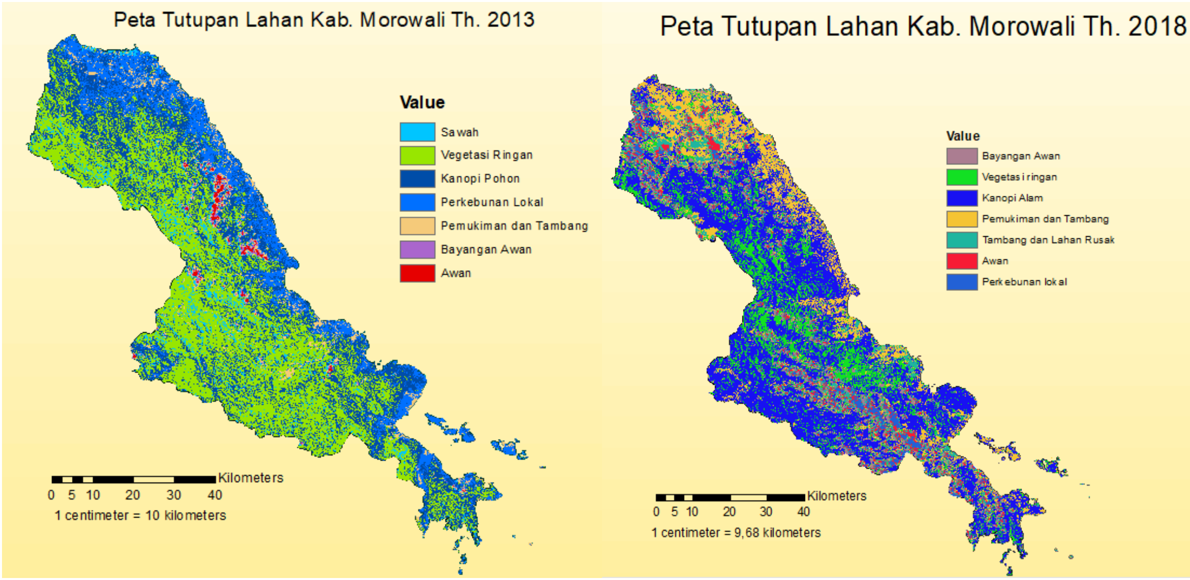

Image 6. Land Cover Map of Morowali Regency in 2013 and 2018

Accuracy Assessment

Accuracy assessment aims to evaluate the precision of results obtained from the *unsupervised classification* method. This assessment is typically presented in the form of an error matrix or confusion matrix, which enables the calculation of various accuracy metrics such as *User's Accuracy, Producer's Accuracy, and Overall Accuracy. Producer's Accuracy* indicates how well the pixels in a given reference class are correctly classified by the model. This metric is associated with *omission error* and is calculated by dividing the number of correctly classified pixels in a class by the total number of actual pixels in that class. *User's Accuracy* reflects the probability that pixels classified into a particular class actually represent that class in the field. This is related to *commission error* and is calculated by dividing the number of correctly classified pixels in a class by the total number of pixels classified into that class. *Overall Accuracy* presents the percentage of total pixels that were correctly classified out of all pixels assessed. This value provides a general overview of the accuracy of the classification results. According to Wulansari [13], classification accuracy can be calculated using a confusion matrix, which facilitates the computation of *producer's accuracy, user's accuracy, overall accuracy*, and the kappa index. Furthermore, Bambang [14] states that image classification is considered accurate if the results from the confusion matrix calculation reach or exceed 80%. Therefore, conducting accuracy assessment using a confusion matrix is crucial to ensure that the applied classification method yields a reliable representation of actual land conditions.

Table 2. Confusion Matrix of Unsupervised Classification in 2018

OID	ClassValue	C_1	C_2	C_3	C_4	C_5	C_6	C_7	Total	User_Accuracy	Kappa
Cloud Shadows	C_1	3	0	0	0	0	0	0	3	1	0
Light Vegetation and Rice Fields	C_2	1	14	0	0	0	0	0	15	93%	0
Forest Canopy	C_3	1	3	19	0	0	0	0	23	83%	0
Settlements and Mining Areas	C_4	0	0	0	4	0	0	0	4	1	0
Mining Sites and Degraded Land	C_5	0	0	0	0	1	1	0	2	50%	0
Cloud	C_6	0	0	0	0	0	2	0	2	1	0
Local Plantations	C_7	0	0	0	0	0	1	0	1	0	0
	Total	5	17	19	4	1	4	0	50	0	0
	Producer_Accuracy	60%	82%	1	1	1	50%	0	0	86%	0
	Kappa	0	0	0	0	0	0	0	0	0	80%

The confusion matrix above illustrates the results of land classification using the unsupervised classification method. This matrix reflects the number of pixels classified into each category compared to the reference data.

The highest user accuracy was observed in the "Light Vegetation and Rice Fields" class (93%) and the "Forest Canopy" class (83%), indicating that most of the pixels classified into these categories correspond to the actual land cover. In contrast, the "Mining and Degraded Land" class exhibited a lower user accuracy (50%), suggesting that some pixels in this class may have been misclassified.

Producer accuracy indicates how well pixels in a reference class were correctly classified by the model. The "Light Vegetation and Rice Fields" class had a producer accuracy of 82%, demonstrating that a large portion of pixels from this class were correctly identified. Conversely, the "Mining and Degraded Land" class had a lower producer accuracy of only 50%.

Overall, the classification results showed an average user accuracy of 86%, reflecting a relatively high level of precision. The Kappa coefficient of 80% also indicates that the classification results are highly accurate and reliable in distinguishing the existing land cover classes.

5. CONCLUSION

This study demonstrates significant land use changes between 2013 and 2018, marked by the expansion of residential and mining areas and the decline of rice fields, light vegetation, natural canopy cover, and local plantations. Industrial expansion and urbanization are identified as the main drivers behind these changes, which impact ecosystem balance, food security, and the risk of ecological disasters.

Stricter spatial planning policies and mitigation efforts such as reforestation and sustainable land management are needed to minimize negative impacts. Future research is encouraged to explore the socio-economic consequences of land use changes and to develop predictive land change models using other machine learning methods to improve classification accuracy.

It is also expected that future studies will extend the analysis to more recent years and incorporate socio-economic components, such as shifts in livelihoods. Technology-based approaches, including advanced machine learning and geospatial analysis, can further enhance the accuracy of predictions and the effectiveness of spatial planning strategies.

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